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Climate Policy Uncertainty and Crude Oil Market Volatility

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In this study, we pursue two main innovations. First, we evaluate the predictive value of climate policy uncertainty (CPU) for oil market volatility. Second, we demonstrate how an investor can exploit the information contents of CPU to gain higher returns. We find that increased values of CPU heighten crude oil market risk, while higher forecast gains are achieved in a model that accommodates CPU. We further show that observing CPU offers higher portfolio returns than ignoring it.

I. INTRODUCTION

The increasing interest to evaluate the connection between climate change and crude oil market is motivated by a number of reasons.¹ First, crude oil consumption (via transportation and electricity, among others) constitutes the largest producer of emissions² and this trend is not likely to abate given higher projected values for oil production in the foreseeable future.³ Second, it appears that various climate regulation policies, such as Green Climate Fund proposition of international tax on crude oil to finance programmes capable of mitigating climate change among others, are not enough to contain greenhouse gas emissions and its attendant impact on climate change. Recent statistics reveal that climate change, if not checked by appropriate policy measures, could push 100 million more people into poverty by 2030.⁴ In addition, while different criteria have been proposed to encourage eco-friendly assets, such as those within the realm of environmental, social, and governance (ESG) investing,⁵ investors need more evidence-based information on how to observe climate change risk in the valuation of assets in order to forestall mispricing due to incomplete information.

Indeed, the literature is replete with studies showing the connection between climate change and energy market (see, for example, Apergis et al., 2022; Gavriilidis, 2021). However, to the best of our knowledge, most of the analyses in the literature are exploratory in nature and where they

are empirical, the results are limited to in-sample predictability and such outcomes may not necessarily translate into out-of-sample forecast gains (Narayan & Gupta, 2015). For practitioners that often rely on projections for investment decisions, extending the analysis to include out-of-sample forecasts is crucial. Specifically, we focus on oil market volatility rather than returns as the ability to maximize returns is usually conditioned on the associated risks and, thus, we formulate a predictive model for oil market volatility in which climate policy uncertainty (CPU) is observed both in the in-sample and out-of-sample cases. Simply, climate policy that seeks to improve the quality of environment tends to reduce oil exploration, thereby dragging down the supply of oil over demand. As a result, the price of oil is expected to rise and its volatility becomes more heightened as consumers and/or producers of crude seek for alternative energy sources.

We employ the mixed data sampling (MIDAS) methodology that accommodates the available “natural” frequencies of the series rather than aggregating or splicing in order to achieve uniform frequency. We offer several robustness tests to validate our results by considering alternative oil price proxies, alternative models in which CPU is replaced with other relevant exogenous factors and distinct analyses for alternative forecast horizons covering short, medium, and long-term forecasts. Finally, we also demonstrate how an investor can exploit the information contents of CPU as well as other relevant information to gain higher returns.

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1 There are recent papers examining the connection between climate risks and financial markets (see Akpa et al., 2022; Lasisi et al., 2022; Oloko et al., 2022).

2 See <https://ourworldindata.org/emissions-by-sector>.

3 See <https://www.eia.gov/todayinenergy/detail.php?id=51318>.

4 See the projection here <https://www.iberdrola.com/sustainability/impacts-of-climate-change>. Also, one of this century's greatest challenges is balancing economic expansion with keeping atmospheric greenhouse gas levels under control (Zeng et al., 2008).

5 See <https://www.investopedia.com/financial-advisor/esg-sri-impact-investing-explaining-difference-clients/>.

Following our experiment with the new dataset (CPU), we report results that further advance the literature on climate change risk and oil market. We show that CPU increases tend to heighten crude oil market volatility. Further analyses show that CPU has predictive contents for the out-of-sample return volatility of crude oil market, while we establish the need for profit maximizing investors to observe CPU when valuing assets.

II. DATA AND METHODOLOGY

A. Data

We utilize monthly CPU index and daily oil price of West Texas Intermediate (WTI) and Brent. The CPU index⁶ developed by Gavrilidis (2021) involves eight leading U.S. newspapers containing some terms relating to uncertainty, regulatory, climatic, and environmental factors in the construction of the index. The oil price data, on the other hand, are sourced from the Federal Reserve Bank of St. Louis.⁷ In terms of scope, the CPU index is from January 2000 to December 2021, while the information on the two oil prices covers the period from 4th January, 2000 through 31st December, 2021. Our start and end dates are conditioned on that of the CPU index.

B. Methodology

We estimate a GARCH-MIDAS variant of MIDAS regressions given that the dependent variable is of a higher (daily) frequency and the exogenous factor is of a lower (monthly) frequency. We favoured this model because it accommodates data in their natural frequency, and, as such, circumvents information loss associated with data aggregation into a uniform frequency (such as splicing of data). Essentially, our CPU data is originally in monthly, while those of WTI and Brent are in daily. Thus, we construct a GARCH-MIDAS-X model of CPU as follows:

$$r_{it} = \varpi + \sqrt{\ell_t} \times s_{i,t} \times \varepsilon_{it}, \quad \varepsilon_{i,t} | \phi_{i-1,t} \square N(0, 1), \quad (1)$$

$$\forall i = 1, 2, 3, \dots, N_t$$

The Eq. (1) is the mean equation, where $r_{i,t}$ is the daily oil price return series computed as the logarithmic return $r_{i,t} = \ln(P_{i,t}) - \ln(P_{i-1,t})$; $P_{i,t}$ represents the price for day i in month t . We specify the conditional variance components for short- and long-run in Eqs. (2) and (3), respectively:

$$s_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \varpi)^2}{\ell_t} + \beta s_{i-1,t} \quad (2)$$

$$\ell_t^{(nw)} = \lambda^{(nw)} + \rho^{(nw)} \sum_{k=1}^K \partial_k(w_1, w_2) \Upsilon_{i-k}^{(n\pi)} \quad (3)$$

where ϖ is the unconditional mean of the return series, as specified in Eq. (1); $s_{i,t}$ is the short-run component with daily frequency, which, as specified in Eq. (2), follows a GARCH(1,1) process, where α and β are the ARCH and

GARCH terms, respectively, conditioned to be positive and/or at least zero ($\alpha > 0$ and $\beta \geq 0$) and the summation yields less than unity ($\alpha + \beta < 1$); and ℓ_t captures the long-run component that incorporates the monthly frequency exogenous macroeconomic series (or realized volatility when there is no macroeconomic series) and involves repeating the monthly value throughout the days in that month.

Finally, we compare the out-of-sample forecast performance of the CPU-based GARCH-MIDAS (GARCH-MIDAS-CPU) model with that of the benchmark model involving realized volatility (GARCH-MIDAS-RV). As a form of additional analysis, we also consider a hybrid index that combines CPU with another important predictor of oil market volatility in recent times, which is the COVID-19 pandemic (see Narayan, 2020; Prabheesh et al., 2020; Salisu & Adediran, 2020, among others) and we utilize, in this regard, the Baker et al. (2020) index technically known as uncertainty due to pandemics and epidemics (UPE) to measure the latter. The hybrid index, described as CPU_UPE in all our results tables, is computed using the principal components analysis (PCA) and the results are suppressed for want of space. Consequently, our forecast evaluation is also extended to the CPU_UPE-based GARCH-MIDAS model and we consider multiple forecast horizons ($h = 30, 60, 120$) all in days, and employ the Harvey et al. (1997) test suitable for non-nested models.

III. RESULTS AND DISCUSSION

We find that the predictability slope coefficient (ρ) is statistically different from zero and contains predictive contents for crude oil volatility, while the relationship is positive (see Table 1). Thus, CPU, especially in the US, can fuel higher uncertainties in the global crude oil market. We also find that the impact of the shock is likely to persist for a while, given that the sum of the ARCH and GARCH effect (α and β) is close to unity. Our out-of-sample forecast outcome shows that, although the proposed model outperforms the benchmark model, it is however more efficient for short-term forecasts. Additionally, we find that, although the hybrid index (CPU_UPE) also has predictive contents for crude oil market volatility, it is not as important as using strictly CPU. This result is very instructive in that it informs the extant literature about the oil market's sensitivity to shock types and emphasizes its ability to differentiate between short-term shocks and long-term structural changes like clean energy adoption. It appears to understand the passing effect of the pandemic and the lasting impact of an alternative energy on oil volatility.

We further evaluate the economic significance of our results by evaluating how an investor can gain a larger proportional increase in portfolio returns by observing CPU and other relevant information (see, for technical details, Campbell & Thompson, 2008). Basically, we compare the

⁶ https://www.policyuncertainty.com/climate_uncertainty.html

⁷ <https://fred.stlouisfed.org/>

Table 1. In-Sample Predictability Results

In-Sample	ϖ	α	β	ρ	w	λ
Brent	0.0007*** [0.0001]	0.0503*** [0.0026]	0.9005*** [0.0055]	6.01e-06** [2.99e-06]	5.0001 [9.2179]	6.48e-05*** [3.85e-06]
WTI	0.0052*** [0.0005]	0.0502*** [0.0077]	0.9002*** [0.0352]	0.0586** [0.0264]	5.0000*** [0.4307]	-0.0157** [0.0070]

Note: α = ARCH term, β = GARCH term, and ρ = slope coefficient. The figures in square brackets are the standard errors of the parameter estimates, while symbols ***, ** and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 2. Out-of-Sample Forecast Evaluation

		Out-of-Sample		
		h=30	h=60	h=120
Brent	CPU	-4.3534***	-3.2299***	-1.9597*
	CPU_UPE	-2.0191**	-1.7321*	-1.6675*
WTI	CPU	-1.8863*	-1.7001*	-1.5943
	CPU_UPE	-1.7283*	-1.5466	-1.4733

Note: Here, we report the test statistics as per Harvey, Leybourne, and Newbold (1997). If the statistic is negative and significant, the GARCH-MIDAS-X (with the exogenous factor, whether CPU or CPU_UPE) is favoured, while the GARCH-MIDAS-RV is chosen if the test statistic is positive and significant. However, if the test statistic is not significant (implying a non-rejection of the null hypothesis), the forecast performance of the two competing models is assumed to be identical. Also, ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

obtained R-squared (R^2) with the squared Sharpe ratio (S^2), as shown by the mean-variance ratio, which serves as a better judge of the magnitude of R^2 in our out-of-sample evaluation [see note to Table 3 regarding these statistics]. We conduct this evaluation over three forecast horizons ($h = 30$ days, 60 days, and 120 days). The decision rule is that the model with the largest mean-variance ratio provides the highest proportional increase in portfolio return for the investor. Our result shows that across the different forecast horizons, portfolio returns can be significantly improved with any of our proposed models, i.e. either one that observes CPU or one that combines CPU and UPE, although the latter gives the highest returns. This implies that, though the CPU_UPE based model may not be as accurate as the CPU model in predicting future returns, its inclusion may yield higher returns. This outcome aligns with the findings of Narayan and Sharma (2014), which show that investors can make substantial gains in returns by using the oil price in forecasting firm return variances.

IV. CONCLUSION

We test the predictive contents of CPU for crude oil market volatility using the GARCH-MIDAS approach. Overall, we find that including the CPU in the predictive model of oil market volatility offers better out-of-sample forecast outcomes compared to the benchmark model that ignores it. We also provide economic significance of our findings using the approach by Campbell and Thompson (2008) and show that investors can use the information in the predictive model to obtain a large proportional increase in their portfolio returns. The outcome offers technical support for observing climate risks, such as those associated with CPU, when taking investment decisions in markets that are among the largest emitters. Therefore, profit maximizing investors are advised to carefully and regularly assess climate-related policy issues that may discourage future investment in the crude oil market and by extension expected gains from such investments.

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Table 3. Out-of-Sample R^2 of Excess Returns

Daily	Forecast horizon (h)	RV				CPU				CPU_UPE			
		Sharp Ratio (S)	S^2	R^2	Mean-Variance ratio (R^2/S^2) %	Sharp Ratio (S)	S^2	R^2	Mean-Variance ratio (R^2/S^2) %	Sharp Ratio (S)	S^2	R^2	Mean-Variance ratio (R^2/S^2) %
Brent	30	0.8403	0.7061	0.3242	45.9139	0.8364	0.6996	0.3265	46.6719	0.8276	0.6849	0.3246	47.3923
	60	0.7608	0.5788	0.3066	52.9701	0.7584	0.5752	0.3075	53.4624	0.7437	0.5531	0.3043	55.0182
	120	0.7422	0.5509	0.3030	55.0048	0.7400	0.5476	0.3034	55.4054	0.7228	0.5224	0.2992	57.2698
WTI	30	0.8747	0.7651	0.3477	45.4450	0.8746	0.7649	0.3484	45.5469	0.8456	0.7150	0.3334	46.6268
	60	0.7783	0.6058	0.3261	53.8340	0.7782	0.6056	0.3267	53.9469	0.7475	0.5588	0.3107	55.6056
	120	0.7576	0.5740	0.3236	56.3805	0.7571	0.5732	0.3236	56.4549	0.7303	0.5333	0.3079	57.7307

Note: RV denotes realized volatility, CPU is climate policy uncertainty and CPU_UPE represents a blend of CPU and uncertainty due to pandemics and epidemics (UPE) using the principal component analysis. Brent is Brent oil returns and WTI is West Texas Intermediate oil returns. Sharpe Ratio (S) = $\mu / (\sigma_x^2 + \sigma_s^2)$, where μ is the fitted average or mean, σ_x^2 is variance of the predictor series, whether CPU or CPU_UPE, σ_s^2 is variance of the residual. Out-of-sample R^2 statistic is computed using $\sigma_x^2 / (\sigma_x^2 + \sigma_s^2)$.



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